Data-Driven Insights for Fetal Health Prediction Using Machine Learning

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1 Introduction

Fetal health monitoring is crucial for early diagnosis of potential complications that could lead to fetal distress or adverse birth outcomes. Current clinical methods often rely on subjective assessment of Cardiotocography (CTG) data, which can result in delayed or inaccurate diagnoses. By leveraging data mining techniques, we aim to enhance predictive modeling for fetal health classification and provide insights into key contributing factors.

2 Research Question

Which CTG features are most predictive of fetal health, and how do traditional and deep learning models compare in classifying fetal health states?

3 Literature Review

[1] The study by Deng et al. (2023) introduces LW-FHRNet, a lightweight fetal distress-assisted diagnosis model that utilizes a cross-channel interactive attention mechanism and wavelet packet decomposition to improve FHR signal classification. Unlike traditional deep learning models that demand high computational resources, LW-FHRNet efficiently transforms one-dimensional FHR signals into two-dimensional feature maps for enhanced pattern recognition while maintaining a small parameter size (0.33M). Achieving 95.24% accuracy on the CTU-UHB dataset, this model demonstrates the feasibility of using lightweight architectures for fetal health monitoring. This research is highly relevant to our study, as it highlights the benefits of feature extraction techniques and efficient classification models in detecting fetal distress. By integrating wavelet packet decomposition and exploring model efficiency, our project can enhance SVM and ANN approaches, leading to improved fetal health classification and real-time clinical applications.

[2] The study by Mandala (2024) introduces a LightGBM-based approach for fetal health classification, achieving 98.31% accuracy by leveraging features such as fetal heart rate, uterine contractions, and maternal blood pressure. It highlights the limitations of traditional CTG interpretation and demonstrates the benefits of feature selection, model optimization, and class balancing using SMOTE. This research aligns closely with our study, which aims to implement SVM and ANN models for fetal health classification. Comparing the performance of LightGBM with SVM and ANN will provide valuable insights into the effectiveness of different classification techniques. Additionally, the study's emphasis on feature importance and preprocessing methods supports our approach in identifying key CTG attributes for better pattern recognition in fetal health assessment. By integrating these findings, our study aims to enhance machine learning-driven fetal health monitoring and improve clinical decision-making.

[4] The study by Sulistianingsih and Martono (2024) explores feature selection techniques and boosting algorithms to enhance fetal health classification using CTG data. By employing RFE and evaluating models like XGBoost, LightGBM, AdaBoost, and CATBoost, the study finds that Random Forest with XGBoost achieves the highest accuracy (95%) and AUC (96%), demonstrating the effectiveness of ensemble learning. It also highlights the importance of feature selection in optimizing model performance and addresses class imbalance challenges using SMOTE. This research is highly relevant to our study, as it provides a benchmark for comparing SVM and ANN models with boosting techniques. Incorporating RFE for feature selection and evaluating cost-sensitive learning as an alternative to SMOTE can improve fetal health classification accuracy and clinical applicability, ensuring a more robust and interpretable predictive model.

[3] The study by Rawat and Mishra (2024) provides a comprehensive review of class imbalance handling techniques, which is crucial for fetal health classification where the number of Pathological cases is significantly lower than Normal cases. The paper explores data-level (SMOTE, undersampling), algorithm-level (cost-sensitive learning), and hybrid approaches, highlighting their impact on classification performance. Notably, cost-sensitive learning, which adjusts model loss functions instead of modifying the dataset, is presented as a viable alternative to SMOTE, making it particularly relevant for SVM and ANN models in our study. The research also discusses evaluation metrics such as AUC-

PR, F1-score, and MCC, which are essential for assessing imbalanced classification performance. By incorporating insights from this study, our project aims to compare SMOTE vs. cost-sensitive learning to determine the most effective strategy for improving fetal health classification accuracy and fairness in machine learning models.

4 Methodology

4.1 Data Preprocessing

Data Cleaning: Handle missing values (if any) and remove inconsistencies in the dataset.
Feature Scaling: Normalize numerical features using StandardScaler or MinMaxScaler to ensure uniform feature ranges.
Handling Class Imbalance: Implement cost-sensitive learning, which adjusts model loss functions to penalize misclassification of minority classes.

4.2 Feature Selection and Extraction

Correlation Analysis: Compute Pearson/Spearman correlations to identify the most relevant CTG features.
Recursive Feature Elimination (RFE): Apply RFE to select optimal features and remove redundant ones.
Dimensionality Reduction: Use Principal Component Analysis (PCA) to improve model efficiency by reducing feature space while preserving variance.

4.3 Model Selection and Implementation

4.3.1 Support Vector Machine (SVM)

Kernel Selection: Utilize Radial Basis Function (RBF) kernel for better classification of nonlinear patterns.
Hyperparameter Tuning: Perform Grid Search to optimize C (regularization), gamma (kernel coefficient), and kernel selection.
Evaluation Metrics: Measure accuracy, precision, recall, F1-score, and AUC-ROC.

4.3.2 Artificial Neural Network (ANN)

Architecture:

- Input Layer: 21 neurons (one per selected feature).
- Hidden Layers: 2-3 fully connected layers with ReLU activation.
- Output Layer: 3 neurons (Softmax activation) for multi-class classification.

Optimizer: Adam
Loss Function: categorical-crossentropy.
Regularization: Apply dropout (0.3-0.5) to prevent overfitting.
Batch Size & Epochs: Tune using cross-validation.

4.4 Novel Techniques

Cost-Sensitive Learning: Instead of oversampling with SMOTE, use cost-sensitive weighting in SVM and ANN to penalize misclassification of minority classes.
Feature Importance Analysis: Use SHAP (SHapley Additive exPlanations) to interpret model decisions and understand which features influence fetal health classification the most.
Comparative Model Analysis: Benchmark SVM and ANN performance against boosting algorithms (XGBoost, LightGBM) using results from previous studies.

5 Expected Experiments and Analysis

Baseline classification performance will be assessed by comparing SVM and ANN models, evaluating their effectiveness in fetal health classification. A feature importance analysis will be conducted to identify key CTG features that contribute most to model predictions. To address class imbalance, cost-sensitive learning and SMOTE will be compared to determine their impact on classification accuracy. Additionally, hyperparameter tuning will be performed to optimize model performance using techniques like Grid Search and Bayesian Optimization. Finally, a comparative evaluation will be conducted using metrics such as accuracy, ROC-AUC, and confusion matrix analysis to determine the most effective classification approach.

6 Project Timeline

Provide a structured timeline of milestones to complete the project within the deadline. Example:

- Week 1: Literature review & dataset collection
- Week 2-3: Data preprocessing & feature selection
- Week 4-5: Implement and train SVM & ANN models
- Week 6-7: Cost-sensitive learning integration & model evaluation
- Week 8: Hyperparameter tuning and refinements
- Week 9: Final report writing and presentation preparation

7 Novelty and Expected Contributions

This study compares SVM and ANN approaches for fetal health prediction, evaluating classification effectiveness. A feature interpretability analysis will identify key CTG attributes, while cost-sensitive learning will improve minority class prediction without altering the dataset. The findings will enhance machine learning applications in fetal health decision support systems, aiding early detection and diagnosis.

8 References

References

[1] Yanjun Deng, Yefei Zhang, Zhixin Zhou, Xianfei Zhang, Pengfei Jiao, and Zhidong Zhao. A lightweight fetal distress-assisted diagnosis model based on a cross-channel interactive attention mechanism. *Frontiers in Physiology*, 14:1090937, March 2023.

[2] Sujith K. Mandala. Unveiling the unborn: Advancing fetal health classification through machine learning. *Artificial Intelligence in Health*, 1:2121, 2024.

[3] Satyendra Rawat and Amit Mishra. Review of methods for handling class-imbalanced in classification problems, 11 2022.

[4] Neny Sulistianingsih and Galih Martono. Enhancing predictive models: An in-depth analysis of feature selection techniques coupled with boosting algorithms. *MATRIK : Jurnal Manajemen, Teknik Informatika dan Rekayasa Komputer*, 23:353–364, 03 2024.

9 Glossary

- AUC - Area Under the Curve
- AUC-PR - Area Under the Precision-Recall Curve
- ANN - Artificial Neural Network
- CTG - Cardiotocography
- CSL - Cost-Sensitive Learning
- FHR - Fetal Heart Rate
- MCC - Matthews Correlation Coefficient
- MBP - Maternal Blood Pressure
- RF - Random Forest
- RFE - Recursive Feature Elimination
- SVM - Support Vector Machine
- SMOTE - Synthetic Minority Over-sampling Technique
- UC - Uterine Contractions
- WPD - Wavelet Packet Decomposition